Modeling Electromagnetic Susceptibility of Processor Using MultiLayer Perceptron

R. M. Alaoui*[1]; L. Bouhouch[2]

Department of Electrical Engineering, University Ibn Zohr, Agadir, Morroco

*[1]r.alaoui@iuz.ac.ma; [2]l.bouhouch@ iuz.ac.ma

Abstract

In this paper, we present an electromagnetic susceptibility study of processors. On a standardized test bench, our investigations have precisely defined the susceptibility and immunity of the microcontroller under test. To predict the resulting power failure at the processor, a model was developed based on multilayer neural networks MLP. The comparative study between experimental observations and the values estimated by our model has a 1.6 of MSE dBm and a 0.99 of regression. In addition to these results, and the stability of our model, in this work the effectiveness of models has been validated based on artificial intelligence, and ease of use by the final user.

Keywords

Susceptibility Electromagnetic; DPI; Multi-Layer Perceptron; MSE, Regression

Introduction

With advances in microelectronics technology and the trend toward miniaturization of integrated circuits, the electronics industry, computing and telecommunications converge on embedded processors connected in networks, especially in the automotive and aerospace *(C.L. Liu & all)*.

Obviously, evolution has enabled lithography manufacturing processors with a frequency more and more important, thus accelerating the processing capacity; unfortunately this is accompanied by a sharp deterioration in the appearance of these electronic systems electromagnetic *(Dominique Paret)*. Figure 1 illustrates the phenomenon of aggression by an electromagnetic disturbance mediated by coupling to an electronic component on a plane.

In this regard, Electromagnetic Compatibility became a normative obligation for which the consumer electronics came into force on 1 January 1996. As an indication, the trend toward smaller dimensions, higher clock frequencies and the increasing complexity of electronic systems, processors behave as switches internal currents up to considerable values, creating an electromagnetic emission (Figure 2) that can affect radio frequency communications, which refers to the security systems by mode coupling leads or radiated. The expertise and knowledge in electromagnetic compatibility level components have become an industrial issue, which has encouraged reconciliation in research and development between industry and academic research laboratories.

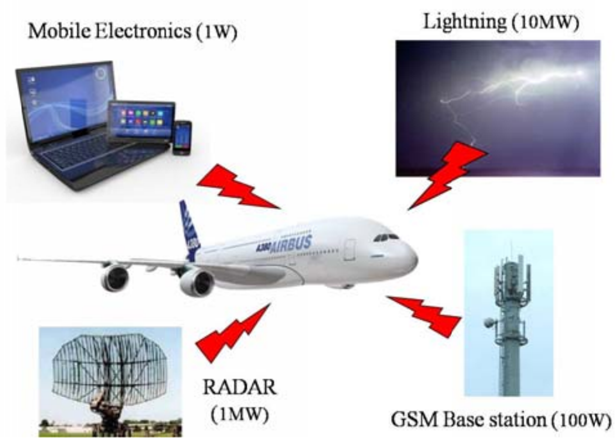

FIG. 1 EXAMPLES OF ELECTROMAGNETIC DISTURBANCES FOR A PLANE

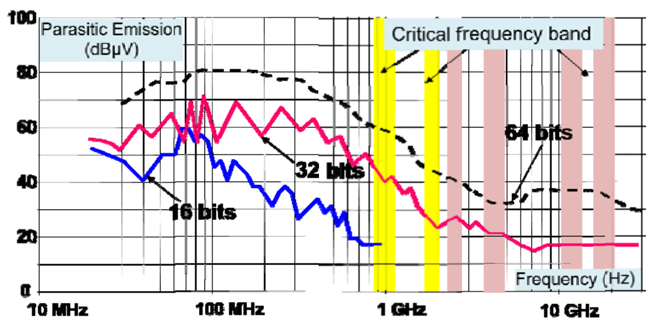

FIG. 2 MICROELECTRONICS EVOLUTION TO SMALL DIMENSIONS, WITH THE INCREASE OF ELECTROMAGNETIC EFFECTS

To help solve this problem for processors, our component under test is developed by the S12X microcontroller Fresscale *(Freescale)*. This is used to drive the intelligent case of constraint (BSI) and currently the heart of integrated vehicle CAN networks providing the roles of coordinator and CAN gateway, system safety, diagnostics, driver assistance, etc. Therefore, it is rec-

ommended to subject the processor installed on a bench complying with EMC requirements, an intense burst of electromagnetic aggression with a standardized method to better define its two spaces: susceptibility and immunity. We explain in the next section the general concept of the evaluation, the worst-case approach used, the method using DPI, the tester and the interpretation of results obtained.

Investigation Tools

In practice, an EMC assessment must follow a defined methodology. Generally, three methods are available for EMC assessment:

- Application of EMC harmonized standards;
- An EMC assessment where no harmonized standards has been applied and the manufacturer applies its own methodology;
- A mixed assessment, combining the above two methods. For example, one can apply the harmonized EMC standards to cover emission phenomena and detailed technical evaluation EMC aspects of immunity.

Only those aspects of immunity will be our investigations.

Worst Case Approach

The EMC assessment will be available when it has been conducted on a configuration producing the maximum disturbance and giving the maximum sensitivity of the device to electromagnetic interference. This method is often called the scenario "worst case" and aims to minimize the costs of the assessment. It is this approach that should be adopted to attack our strong component under test during the experiment *(Guide d'application)*.

Test Bench Methods and Measurement Results

The evaluation of the sensitivity of components required the development and standardization of specific methods, grouped under the *(IEC-62132-2)*. These methods differ in the technique used to inject the disturbance in the circuit. As well in the type of coupling leads or radiated fields and the frequency of use. The method we use for this study is the method-Power Direct-Injection (DPI), characterized by simplicity, inexpensiveness, expandability to 10 GHz. Its implementation is described in Figure 3. A signal controlled by computer is amplified before injected by capacitive coupling on the component. A measure of a real-time processor output alerts the measuring device when the signal is out of range (time and voltage) of a predefined template.

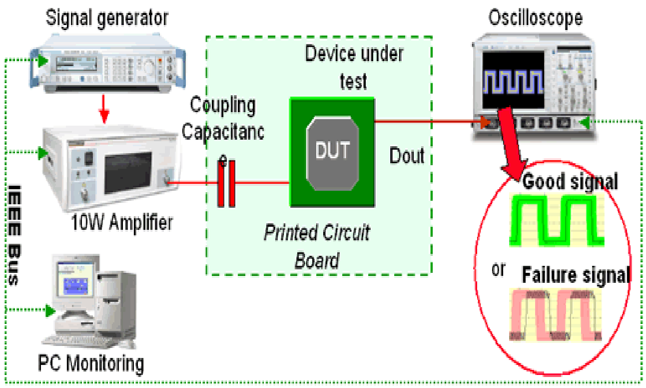

FIG. 3 PRINCIPLE OF DPI BENCH INJECTION

Figure 4 illustrates a sample of those things or each point corresponding to a vector susceptibility characterized by a forward power of aggression expressed in dBm for a given frequency.

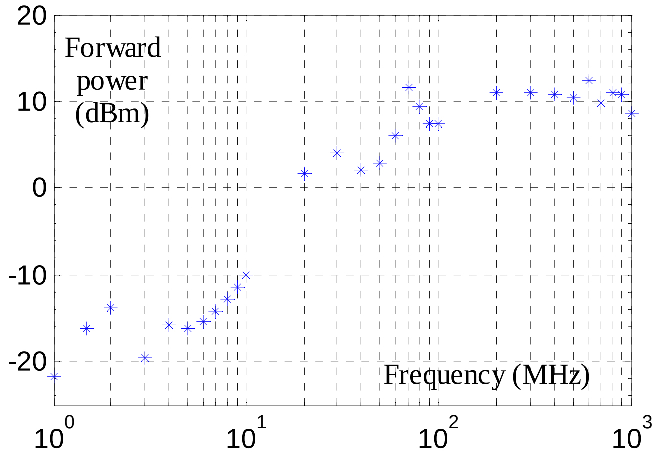

FIG. 4 SUSCEPTIBILITY OF S12X MICROCONTROLLER

All vectors of susceptibility, with powers equal and greater as indicated on the curve with their respective frequencies, are the space of the processor which induces susceptibility to deterioration during its service life. However, the processor immunity is represented by vectors with powers below the previous space vectors with the same frequency. A brief reading of the measured values shows that the variation in susceptibility and/or immunity of the device under test is not linear.

Note that the dBm (sometimes dBmW) is an abbreviation of the power ratio in decibels (dB) between the measured power and one milliwatt (mW). It is used in radio networks, microwave and optical fiber as a convenient measure of absolute power because of its ability to express both very large values and very small in abbreviated form. There are also dBmW, which are reported to one watt (1000 mW).

Modeling

Electromagnetic Compatibility EMC is based on Maxwell's equations, which give a precise mathematical framework and the basic concept of field in physics introduced by Faraday in the 1830s. In the most general case, we must speak of the electromagnetic fields, some of which identify with those components of the electric field and others to those of the magnetic field. But this synthesis of the electromagnetic phenomenon is more in transmission and susceptibility that has been little researched. Our investigations, using the method DPI, have identified two areas of susceptibility and immunity of the device under test. It is seen in section models that the hyper plan would be determined that separates the two areas experienced.

Mathematical Modelling

Research on the mathematical model, corresponding to the susceptibility, is to determine an unknown function f(x) explicitly, but only at certain frequencies known evaluable by an expensive computation. Our principle in this work is to identify f by a simple function, easy to evaluate. The problem is the existence of an infinite family of solutions by polynomial functions, exponential and trigonometric.

According to Weirstrass Approximation Theorem, any function continuous over a closed interval can be approximated arbitrarily well by polynomials. The theorem, nevertheless, does not tell us how to construct such a polynomial to satisfy a specified error range allowed for approximation. In addition, polynomial interpolation does not fit any continuous function properly. Also in the case of equally spaced nodes, polynomial interpolation may become unstable

In general, *(Tam, K.Y & all*) compared the performance of neural networks to that of other techniques such as interpolation analysis and found that neural networks outperform other techniques.

Modelling by Multilayer Neural Network

To better evaluate the electromagnetic susceptibility of our microcontroller, the model has been developed based on networks neurons as shown in Figure 5.A neural network is a statistical analysis tool to build a model of behaviour from a series of experimental observation, and consists of a directed weighted graph whose nodes symbolize the neurons having an activation function that can influence other neurons in the network. Connections between neurons, known as synaptic connections, spread the activity of neurons with a weighting characteristic of the connection. Synaptic weight is called the weighting of synaptic connections.

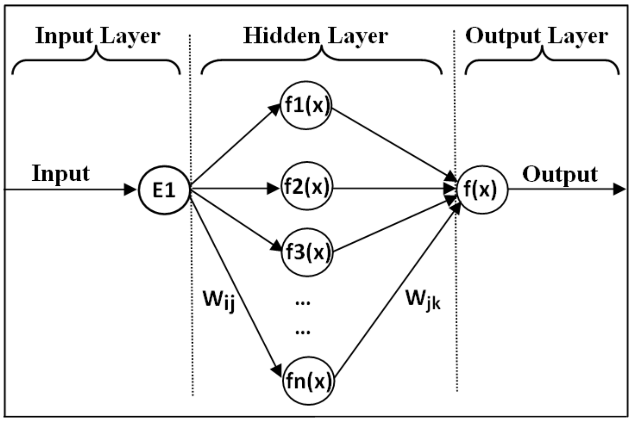

FIG. 5 MULTILAYER NEURAL NETWORK MLP

In this section programs of multilayer neural networks MLP in Matlab have been developed, in which the back propagation gradient is applied to identify different curves that best represent our experimental data of susceptibility.

To evaluate the performances of our model, the Root Mean Squared Error (RMSE) and the regression analysis are employed.

In science field, the use of RMSE is very common and it makes an excellent tool of error metric for numerical predictions.

The popular formula of RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_i (p_i - a_i)^2} \quad (1)$$

Where: a: Actual target; p: Predicted target.

An MSE of zero, meaning that the estimator p predicts observations of the parameter a with perfect accuracy, is the ideal, but practically never possible. Minimizing MSE is a key criterion in selecting estimators.

While regression analysis is used, to find equations that fit data. Once the equation is acquired, the model can be utilized to make predictions. One type of regression analysis is linear analysis. When, the correlation coefficient shows that data is likely to be able to predict future outcomes.

The most common method for fitting a regression line is the method of least-squares which calculates the best-fitting line for the observed data by minimizing the sum of the squares of the vertical deviations from each data point to the line.

The least squares regression line is a mathematical model for the data, and the line that makes the sum of

the squares of the residuals as small as possible. When, *a* residual is a difference between an observed *y* and a predicted *y*, the equation of the least squares regression line of *y* on *x* is:

$$y - \bar{y} = b(x - \bar{x}) \tag{2}$$

Where b is:

$$b = \frac{S_{xy}}{S_{xx}} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} = \frac{\frac{\sum x_i y_i}{n} - \bar{x}\bar{y}}{\frac{\sum x_i^2}{n} - \bar{x}^2} \tag{3}$$

Note that *b* is slope and *a* is the *y*-intercept. where $\bar{x}, \bar{y}$ are the mean of the observed *x* and *y* data and n is the number of data pairs (x_i, y_i).

The fraction of the total variation in the dependent variable that is explained by the independent variable is known as the coefficient of determination R^2, which is calculated as:

$$R^2 = 1 - \frac{SEE}{TSS} \tag{4}$$

Where SSE, the sum of squares errors, is given by:

$$SEE = \sum_i^{=} (y_i - \hat{y}_i)^2 \tag{5}$$

And TSS, the total sum of squares, is given by:

$$TSS = \sum_i^{=} (y_i - \bar{y})^2 \tag{6}$$

And where $\hat{y}_i$ are the predicted *y* values at each x_i:

For simple least squares regression (i.e. only one independent variable), the square root of R^2 is equivalent to the simple correlation coefficient *r*. That one may alternatively be calculated as:

$$r = \frac{S_{xy}}{S_{xx}} = \frac{(\sum_i (x_i - \bar{x}))(\sum_i (y_i - \bar{y}))}{\sqrt{(\sum_i (x_i - \bar{x})^2)(\sum_i (y_i - \bar{y})^2)}} \tag{7}$$

r provides a quantitative measure of the linear relationship between *x* and *y*, ranging from -1 to +1: a value of *r* = -1 or +1 indicates a perfect linear fit, and *r* = 0 indicates that no linear relationship exists at all.

As $\sum_i (y_i - \hat{y})^2$ the sum of squared errors between the observed and predicted y-values, tends to zero, so r^2 tends to 1 and therefore *r* tends to -1 or +1, its sign depends on whether *b* is negative or positive respectively.

Results and Discussions

Before the use of the classification capabilities of a neural network, the structure has been built for our experimental database (training set and test set), and then the network was set up by using an algorithm to learning the recognition phase *(Gérard Dreyfus and all)*.

Indeed, the recognition phase, is based on the Levenberg-Marquardt (Michael Lamptona) in our case, and the network is to present each of the vectors of the test database. Levenberg uses the second derivative of a function to reduce the number of iterations of an optimization algorithm. The corresponding output is calculated by propagating the vector through the network. The response of the array is read directly from the output units and compared to the expected answer. Once the network has acceptable performance, it can be used to meet the need behind its construction. A target data vector is experimental data used on training or validation. Output data vector is response of the model that is composed of three neurons in hidden layer. To evaluate our model, the simulation has been performed in two stages. The first stage is training model where the simulator returned experimental observations as follows: 70% for training, 15% for testing and 15% for the validation stage. In the second stage we call validation which our own verification has been implemented to evaluate the model using experimental observations which were not used in the first stage. Figure 6 shows the results obtained in stage 1 by our model under training. The target data vector is our experimental forward power used for training versus their frequencies. The susceptibility prediction by our model varies from -18 dBm to 10 dBm (forward power).

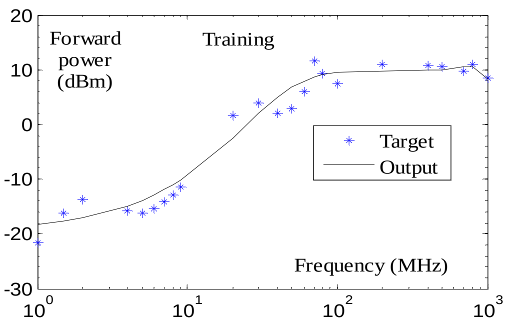

FIG. 6 MLP TRAINING

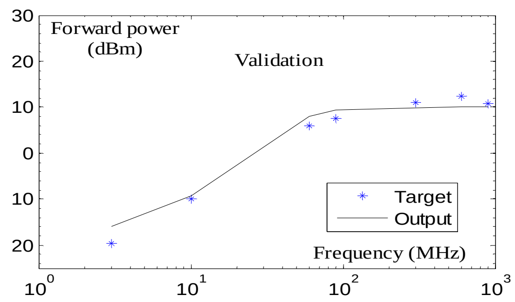

FIG. 7 MLP VALIDATION

In the second stage, the simulation results of validation model are presented in the figure 7 showing that

our model follows the experimental observations.

Figure 8 shows the error estimating the deviation between the experimental observations (Target) and outputs predicted by the MLP during both stages.

Curve (a) describes the error in training stage that ranges from -4 to 4dBm with 0.71dBm of RMSE, while curve (b) shows the error in the validation stage that ranges from -3.4dBm to 2dBm with 23.10^{-3}dBm of RMSE.

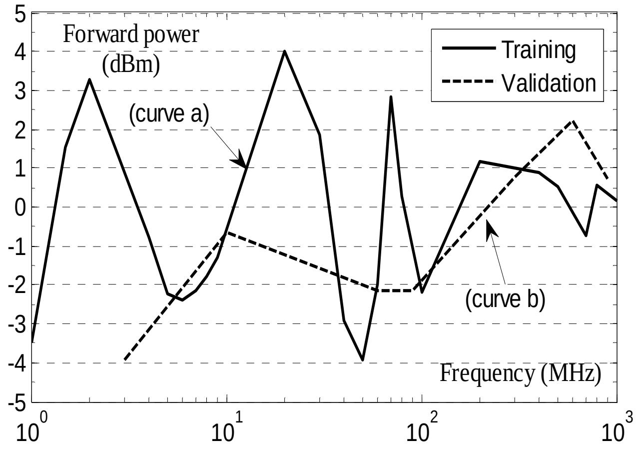

FIG. 8 COMPARISON OF MODEL ERRORS AT BOTH STAGES

The figure 9 shows the graphs of regression model R for the different phases of the simulation stage 1: R is 0.98 for the training phase, 0.99 for validation and testing phases. After adjusting the parameters (weights) was made, the network neurons has a capacity of generalization of data not present in the training set evaluated by 0.98 of regression.

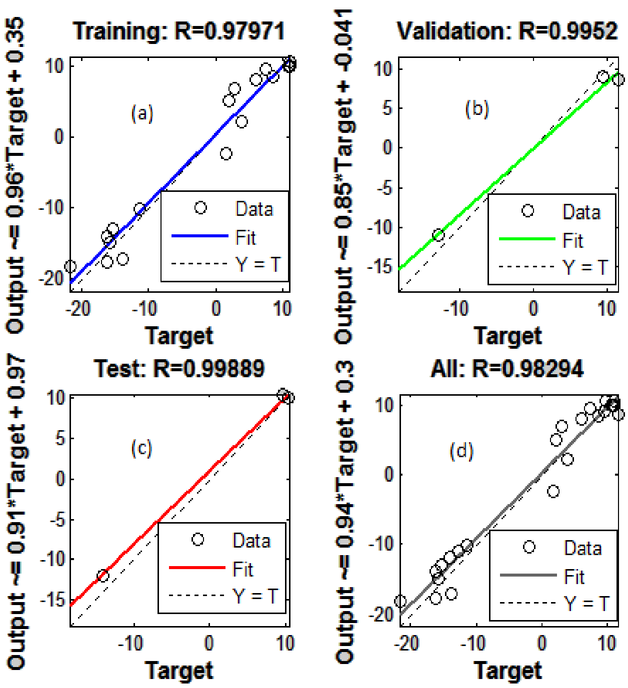

FIG. 9.REGRESSION OF MODEL IN FIRST STAGE

MLP is fast when running determined with nonlinear functions of linear combinations *(C.L. Liu)*. This allows the use of feature vectors large enough, increasing the discriminating power of the classifier. Moreover, they allow obtaining the output of probabilities, which is valuable to interpreting the results.

The implementation of an MLP is easy, and usually gives satisfactory results. Neural networks, due to their structure, are able to determine the boundaries of complex decision.

The big problem is that the MLP cannot know a priori the size of the network for a given problem. Experience shows that it is not necessary to have more than one hidden layer for the best results *(J. Liu)*. However, we cannot determine in advance the number of neuron in the hidden layer required for a given problem.The adjustment of connection weights is also difficult to optimize, and it is necessary to set these parameters by trial and error, ie we look at the behaviour of the network based learning, and choose the best configuration. In addition, the number of iterations during the learning phase is a parameter which must be found empirically. This one is important as it appears after a certain number of iterations the well-known phenomenon of over-learning, in which the MLP begins to learn by heart the examples in the training set and loses its ability to generalize. Using a validation dataset, we can calculate the generalization error of the network depending on the number of iterations. In addition the number of iterations has been naturally selected that minimizes the generalization error. Thus a limitation of the MLP is that it requires substantial foundation for learning.

Conclusion

In this work, we set the standard method of measuring the electromagnetic susceptibility of a microcontroller used for critical applications with elevated level of safety, and then the MLP network with one hidden layer of only three neurons to model the phenomenon of susceptibility of our microcontroller under test. Graphs illustrating both developed simulation stages show the stability of this model. Once the elaboration phase of the model and learning taking some time are made, the electromagnetic susceptibility is predicted. According to the results obtained, it can be noted that our model based on artificial neural networks is the best tool to model susceptibility and immunity EMC electromagnetic integrated circuits.

ACKNOWLEDGMENT

The authors would like to thank Etienne Sicard and

Alexandre Boyer (INSA, Toulouse, France) for their valuable discussions and support, as well as Stephane Baffreau (IUT Tarbes, France) for their help with setting up the DPI test bench.

REFERENCES

C.L. Liu, K. Nakashima, H. Sako, H. Fujisawa. "Handwritten digit recognition using state-of-the-art techniques", IEEE, 2002.

Dominique Paret, "Réseaux multiplexés pour systèmes embarqués CAN, LIN, FlexRay, Safe-by-Wire", Dunod, 2004.

Freescale, Microcontrôleur S12X, www.freescale.com, 2005.

Gérard Dreyfus and all "Apprentissage statistique Réseaux de neurones - Cartes topologiques - Machines à vecteurs supports", Edition EYROLLES Collection, Algorithmes, 2008.

"Guide d'application de la directive Européenne sur la CEM 2004/108/CE", http:// cmrt.centrale-marseille.fr/ electromagnetisme/ veille/guide_2004_108_francais.pdf, (27 février 2007).

H.A. Thompson, "A CAN bus-based safety-critical distributed systems", Microprocessors and Microsystems, 345-355, 2006.

IEC 62132- 2 "Direct RF power injection to measurement method", 2005.

J. Liu, P. Gader, "Neural networks with enhanced outlier rejection ability for off-line handwritten word recognition," Pattern Recognition, 2002.

Michael Lamptona "Damping–undamping strategies for the Levenberg–Marquardt nonlinear least-squares method", Center for EUV Astrophysics, University of California, Berkeley, California 94720-5030, 1996.

Tam, K.Y. and M.Y Kiam, "Managerial applications of neural networks: the case of bank failure predictions", Management science, Vol. 38 n 7, 926-947, July 1992.

Rachid Alaoui is a professor at the ESTA (Ecole Supérieure de Technologies d'Agadir), Morocco. He received the BS degree in electronics engineering from ENSET, Rabat, Morrocco, in 1986, He received the MS degree in process engineering from ENSA, Agadir, Morrocco, in 2006, and the PhD degree in defensive software, from Ibn Zohr University, Agadir, Morrocco. He is a research associate at the Centre for Compatibility Electromagnetic of Integrated Circuits, Lattis, INSA, and Toulouse, France. His research interests include Fault-Tolerant computing, Reliability, and Processor Susceptibility.

Lahoussine Bouhouch is a professor at the ESTA (Ecole Supérieure de Technologies d'Agadir), Morocco. He holds a Masters Degree and the PhD in Electronic engineering, from the University of Nancy I, France, in 1985 and 1988 respectively. He also holds a state thesis in Electronic, from the University Ibn Zohr of Agadir, Morocco in 2007.

In research, it is interested in electromagnetic compatibility (EMC), while characterizing and by modelling the interaction between magnetic materials and the processors.

He works in close cooperation with the platform of research in EMC component of the LATTIS, INSA, Toulouse, France.